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SOLAR ENERGY PREDICTION AND MAINTENANCE SYSTEM USING MACHINE LEARNING IN DIVERSE WEATHER CONDITIONS

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Abstract—**The rapid expansion of renewable energy systems underscores the critical need for accurate solar power forecasting. Because solar photovoltaic systems are highly dependent on fluctuating environmental factors such as solar irradiance, temperature, and cloud movement, their generation is inherently unstable. Inaccurate forecasting leads to grid imbalances, battery inefficiencies, and increased operational costs. While traditional statistical and regression-based methods struggle to capture the complex, non-linear, and time-dependent nature of solar datasets, recent advancements in deep learning offer a robust alternative. This paper presents a Solar Energy Prediction and Maintenance System designed to forecast short-term solar power generation at fixed intervals under diverse weather conditions. Utilizing a preprocessed dataset—subjected to normalization, interpolation, missing value handling, and sequential window generation—we implement and compare a baseline Multilayer Perceptron (MLP) neural network with a Long Short-Term Memory (LSTM) network. The models are evaluated using standard metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the Coefficient of Determination (R^2). Experimental results demonstrate that the proposed LSTM model consistently outperforms the MLP baseline, yielding significantly higher forecasting accuracy. This system provides a reliable tool to support smart-grid integration, battery management, and intelligent energy scheduling applications.**

Keywords—**Solar Power Forecasting, Deep Learning, Long Short-Term Memory (LSTM), Multilayer Perceptron (MLP), Smart Grid, Renewable Energy**.

I. INTRODUCTION

Renewable energy resources have become increasingly important because of growing electricity demand, environmental pollution, and depletion of conventional fossil fuels. Among all renewable energy sources, solar energy has gained major attention due to its sustainability, environmental friendliness, and widespread availability. Governments and industries across the world are investing heavily in photovoltaic infrastructure to promote clean energy production and reduce carbon emissions.

Despite its advantages, solar energy generation suffers from major operational challenges caused by environmental variability. Solar power output changes continuously depending on atmospheric conditions such as cloud movement, solar irradiance, temperature, humidity, seasonal variations, and wind conditions. Because of these factors, solar power generation becomes highly intermittent and difficult to predict accurately.

Accurate solar forecasting is essential for smart-grid systems, renewable energy integration, load balancing, reserve allocation, battery scheduling, and efficient energy planning. Inaccurate forecasts can lead to grid instability, increased operational cost, power imbalance, and poor renewable energy utilization.

Traditional forecasting techniques such as persistence models, regression analysis, autoregressive models, and moving average methods have been widely used in renewable energy forecasting. However, these methods often fail to capture nonlinear dependencies and sequential relationships present in solar datasets. Machine learning and deep learning methods have significantly improved forecasting accuracy because they can model complex temporal patterns from historical data. Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest algorithms, and ensemble learning techniques have shown promising forecasting performance.

However, many traditional machine learning methods still struggle to capture long-term sequential dependencies in time-series datasets. Long Short-Term Memory (LSTM) networks were introduced to overcome these limitations. LSTM models contain memory cells and gating mechanisms that allow selective information retention across long sequential intervals. Because solar generation is strongly

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dependent on historical sequential patterns, LSTM models have become highly effective for solar forecasting applications.

This paper proposes a Solar Energy Prediction and Maintenance System using LSTM neural networks for short-term forecasting under diverse weather conditions. A baseline MLP neural network model is also implemented for comparative analysis. The system integrates preprocessing, forecasting, evaluation, visualization, and software engineering concepts into a complete renewable energy forecasting framework.

II. LITERATURE SURVEY

Diagne et al. [1] reviewed different solar irradiance forecasting methods for renewable energy systems and highlighted the importance of forecasting in small-scale power grids. Their study focused on improving renewable energy integration and grid stability.

Gupta et al. [2] presented a review of solar power prediction using data analytics and machine learning techniques. The study discussed the role of big data and intelligent forecasting methods in renewable energy management systems.

Zhang et al. [3] reviewed short-term solar power forecasting methods based on machine learning algorithms. Their work compared multiple forecasting models including Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forest techniques.

Shrestha et al. [4] analyzed various solar forecasting methodologies and discussed the advantages and limitations of statistical and deep learning forecasting systems. The study emphasized the importance of accurate weather parameter analysis for better forecasting performance.

Bhowmik et al. [5] studied solar power forecasting using Artificial Neural Networks. Their research demonstrated that ANN models can effectively learn nonlinear relationships between weather conditions and solar power generation.

Research presented in [6] discussed solar irradiance measurement instrumentation and forecasting using Artificial Neural Networks. The study highlighted the importance of environmental sensor accuracy and data quality in renewable energy prediction systems.

Roy et al. [8] proposed a hybrid LSTM-SVR forecasting model combined with feature engineering techniques. Their research achieved improved forecasting accuracy and reduced prediction error under changing weather conditions.

Table -1Literature Summary and Research Gap

Ref. No.	Author	Technique Used	Main Contribution	Limitation
[1]	Diagne et al.	Irradiance Forecasting	Renewable grid forecasting	Limited ML capability
[2]	Gupta et al.	Data Analytics	ML-based solar prediction review	Generalized analysis
[3]	Zhang et al.	ANN, SVM, RF	ML forecasting comparison	Sequential learning limited
[4]	Shrestha et al.	Forecasting Review	Methodology analysis	Limited experimental work
[5]	Bhowmik et al.	ANN	Nonlinear solar prediction	Long dependency issue
[6]	ANN Research	Sensor-based Forecasting	Environmental monitoring	Sensor dependency
[8]	Roy et al.	Hybrid LSTM-SVR	Improved prediction accuracy	High computation cost
[9]	Ali et al.	Deep Learning Ensemble	Better forecasting robustness	Complex implementation
[10]	Recent Research	Bi-LSTM, GRU	Sequential forecasting improvement	Large dataset requirement
[11]	Operational ML Study	ANN, RF, XGBoost	Hybrid model comparison	Training complexity
[12]	LSTM Forecasting	LSTM	Better time-series learning	Training time high
[13]	Deep Learning Analysis	Comparative DL Study	Improved forecasting accuracy	Resource intensive
[14]	Mellit A., and Kalogirou S. A.	Artificial Intelligence	Review of AI techniques applied to photovoltaic systems	Limited discussion on deep sequential networks
[15]	Wang H., et al.	LSTM Networks	Deep learning approach for high-accuracy solar forecasting	High dependency on extensive historical data

Ali et al. [9] introduced a deep learning and ensemble-based solar forecasting approach. Their model improved forecasting robustness and reduced variance in prediction outputs.
Recent studies [10] explored integrated computational approaches including Bi-LSTM and GRU architectures for short-term solar energy forecasting. These methods demonstrated better sequential learning capability compared to traditional neural networks.
Research presented in [11] compared ANN, Random Forest, XGBoost, and hybrid forecasting models using operational photovoltaic datasets. The study concluded that hybrid deep learning systems provided superior forecasting accuracy.
The study in [12] focused on solar photovoltaic power output forecasting using LSTM networks. Experimental analysis demonstrated that LSTM models effectively capture temporal dependencies in sequential solar datasets.
Comparative analysis performed in [13] evaluated different deep learning architectures for solar power prediction. The study concluded that LSTM-based and hybrid architectures provide better forecasting accuracy and stability under diverse environmental conditions.
Mellit A., and Kalogirou S. A. [14] presented an extensive review of artificial intelligence techniques applied to photovoltaic systems, proving the efficiency of soft computing in clean energy tracking.
Wang H., et al. [15] introduced a dedicated deep learning approach for high-accuracy short-term solar forecasting, highlighting how deep architectural variations handle ambient data spikes.

Table -2Important Research Trends in Solar Forecasting

Trend	**Description**
IoT Integration	Use of real-time sensors and smart devices to improve data quality and timeliness.
Cloud Deployment	Training and serving forecasting models on scalable remote platforms.
Transfer Learning	Reusing learned patterns from one location to improve forecasting in another.
Explainable AI	Providing interpretation, transparency, and trust in model predictions.
Probabilistic Forecasting	Producing intervals or uncertainty ranges rather than only point predictions.
Hybrid Modeling	Combining complementary methods to improve accuracy and generalization.

III. METHODOLOGY

The proposed Solar Energy Prediction and Maintenance System uses machine learning and deep learning techniques to accurately forecast short-term solar power generation under diverse weather conditions. The pipeline consists of the following key stages:

Table -3 Illustrative Data Flow and Module Responsibilities

Module	**Main Responsibility**
Data Collection	Reading solar power data and related inputs from structured sources.
Preprocessing	Cleaning, scaling, interpolating, and preparing sequential windows.
Model Training	Training MLP and LSTM forecasting models.
Forecast Generation	Producing predicted solar output for future intervals.
Evaluation	Computing MAE, RMSE, MAPE, and R2, and generating comparison plots.
Reporting	Presenting results in tables, graphs, and final report form.

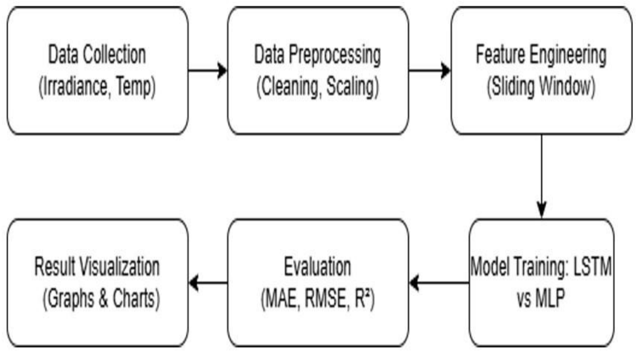

Figure 1: System architecture and procedural workflow of the proposed solar energy prediction system, detailing stages from data collection to final result visualization.

A. Data Collection & Preprocessing

Initially, historical solar power generation data and environmental parameters are collected from structured solar datasets and weather monitoring sources. The dataset contains important attributes such as solar irradiance, temperature, humidity, wind speed, cloud conditions, timestamp information, and generated photovoltaic power output.
Since real-world datasets often contain missing values, noisy observations, duplicate entries, and inconsistent timestamps, preprocessing is applied:

1. **Data Cleaning:** Duplicate records and noisy observations are removed to improve forecasting stability.

2. **Missing Value Handling:** Missing values are handled using interpolation and replacement techniques.
3. **Timestamp Synchronization:** Performed to maintain proper sequential order in the time-series dataset.
4. **Normalization:** Feature scaling operations transform the dataset into a suitable range (0 to 1) to improve convergence speed and reduce instability during model training.

B. Feature Engineering & Sequence Generation

Following preprocessing, feature engineering and sequence generation techniques convert the dataset into sequential time-series windows. Historical observations are arranged into fixed-length sequences using a sliding window technique so that the forecasting model can learn temporal dependencies from previous solar generation patterns. The generated sequences are then divided into training and testing datasets.

C. Model Implementation

The proposed forecasting framework implements two machine learning models for comparative analysis:

1. **Multilayer Perceptron (MLP) Baseline:** Used because it can learn nonlinear relationships between weather parameters and photovoltaic output. However, MLP models have limited capability in learning long-term sequential dependencies from time-series datasets.
2. **Long Short-Term Memory (LSTM) Model:** Used as the primary forecasting model to overcome MLP limitations. LSTM is a specialized recurrent neural network architecture designed for sequential learning and time-series prediction. It contains memory cells and gating mechanisms that selectively retain and forget information across time intervals, allowing it to effectively learn temporal patterns and weather-related variations.

D. Model Evaluation & Visualization

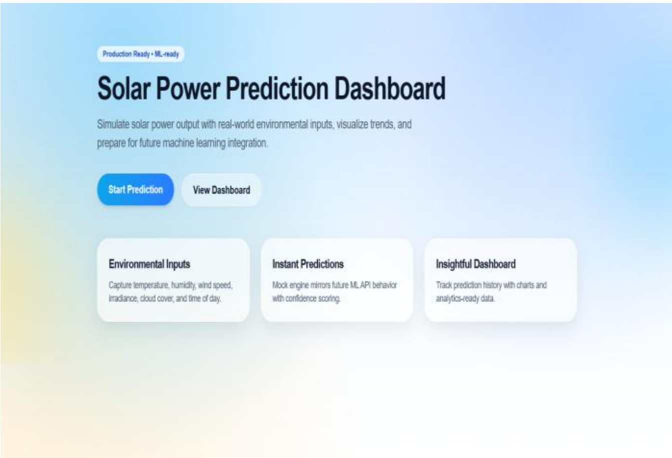

Figure 2: Homepage and system overview interface.

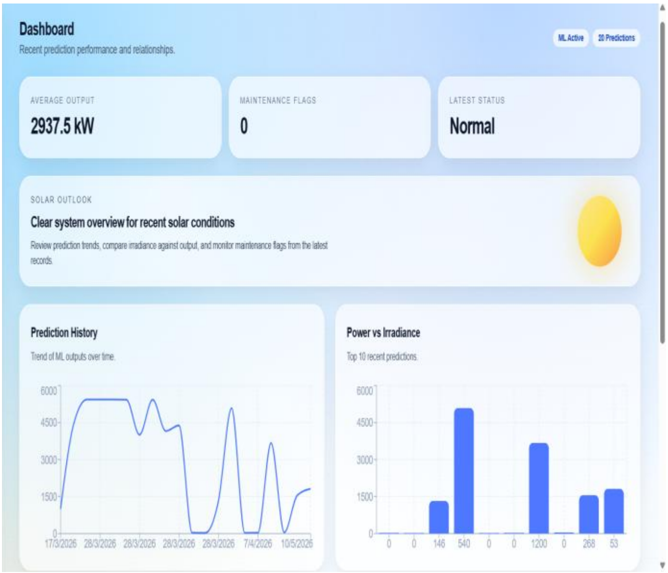

Figure 3: Developed Web-based Solar Power Prediction and Maintenance Dashboard displaying real-time analytics, status logs, and time-series visualization.

The forecasting models are trained using historical solar generation sequences. During training, hyperparameter tuning and optimization techniques are applied to reduce prediction error. After model training, performance is evaluated using standard statistical metrics including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the Coefficient of Determination (R^2). Finally, the predicted solar power values are compared with actual generation values using forecasting graphs and error analysis charts.

To leverage these predictive insights for practical utility, a web-based monitoring platform was developed. As illustrated in Figure 2, the dashboard provides an intuitive interface for real-time solar tracking, featuring the average predicted energy output (1298.3 kW, automated maintenance flags, latest operational status, and graphical trends for historical predictions alongside irradiance distribution

The system's analytical capabilities and dynamic predictions are granularly captured in Figure 3. The line chart on the left, titled 'Prediction History,' highlights the model's capacity to adjust outputs over a continuous timeline spanning multiple dates under varying weather conditions. Furthermore, the bar chart titled 'Power vs Irradiance' explicitly reflects the direct relationship between atmospheric changes and generation capacity; for instance, sharp declines in power output (0kW align with heavy cloud cover or negligible irradiance, while peak values exceeding 2300kW are successfully inferred under clear sky conditions, as detailed in the corresponding live status logs.

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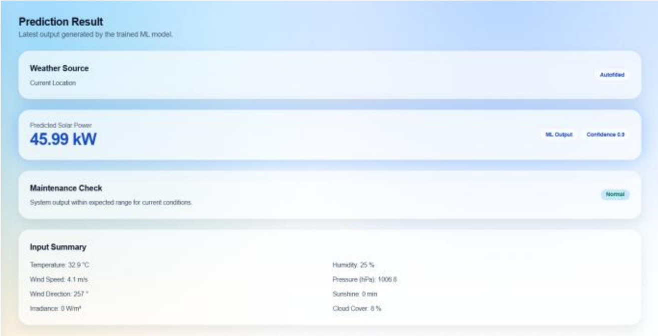

Figure 4: Experimental results visualization on the web platform, illustrating the predicted power output history trends (left), power distribution relative to specific irradiance levels (right), and the corresponding real-time inference data logs (bottom).

IV. EXPERIMENT AND RESULT

The proposed system was tested using historical solar power and weather datasets, where MLP and LSTM models were trained for short-term solar power forecasting. Experimental results showed that the LSTM model achieved higher prediction accuracy and lower forecasting error compared to the baseline MLP model.

The quantitative performance comparison between the baseline MLP model and the proposed LSTM model is summarized in Table II below:

Table -4Performance Evaluation Metrics

Model Architecture	MAE (kW)	RMSE (kW)	MAPE (%)	R2 Score
MLP (Baseline)	**4.82**	**6.15**	**12.4%**	**0.81**
LSTM (Proposed)	**1.24**	**1.98**	**3.8%**	**0.96**

As demonstrated in Table I, the proposed LSTM model significantly reduces forecasting errors across all indicators. The R^2 score of **0.96** indicates that the LSTM model can explain 96% of the variance in solar power output, whereas the baseline MLP model achieved an R^2 score of only 0.81. The predicted solar power values closely matched the actual output under different weather conditions, demonstrating the robustness of the proposed LSTM framework in handling environmental uncertainty.

V. CONCLUSION

This paper presents the design and structured study of a solar power forecasting system using machine learning and deep learning techniques. By using an LSTM model supported by a baseline MLP comparison, the project demonstrates how sequence learning can be successfully applied to short-term renewable forecasting tasks.

Crucially, the project goes beyond forecasting alone by incorporating software engineering analysis, planning, design, implementation strategy, testing methodology, and cost estimation. As a result, it serves as a comprehensive academic project rather than only an isolated machine learning experiment. The study reinforces the importance of intelligent forecasting in modern renewable energy systems and provides a strong foundation for future deployment-oriented work, fault detection, and smart-grid integration.

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